Sign-Language Datasets at Scale: A Comprehensive Survey on Resources, Benchmarks, and Annotation Standards

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Abstract

Sign languages are expressive visual languages used by Deaf and Hard-of-Hearing (DHH) communities. Despite advances in sign-language recognition, translation, and production, progress remains limited by fragmented datasets, inconsistent annotations, and narrow linguistic coverage. Existing benchmarks often fail to support real-world communication needs, and systematic analyses of their limitations are rare. In this survey, we present the most comprehensive index of sign-language datasets to date, covering 120 resources across 35 sign languages, and identify key challenges including modality imbalance, annotation granularity, and signer bias. We propose essential requirements for future datasets and introduce a 24-field *Sign-Language Datasheet* template, along with a public GitHub repo[1] for dataset documentation. Our work provides a unified foundation for developing inclusive and robust sign-language technologies.

1 Introduction

Sign languages are fully developed visual-gestural languages that serve as the primary means of communication for over 70 million Deaf and Hard-of-Hearing (DHH) individuals worldwide (Organization). Unlike spoken languages, they convey meaning through integrated manual articulations (handshape, location, movement, orientation) and non-manual cues such as facial expressions, mouthing, gaze, and body posture (Boyes-Braem and Sutton-Spence, 2001). Despite their linguistic complexity and expressive power (Jachova et al., 2008), sign languages are often misunderstood, and proficiency typically requires years of practice (Kemp, 1998). As a result, fluency among hearing populations remains rare, reinforcing communication barriers between DHH and hearing communities.

[1] https://anonymous.4open.science/r/Open-Sign-Language-9D59/README.md

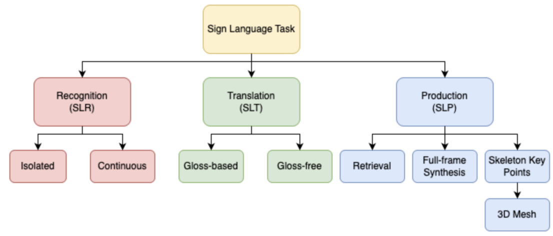


Figure 1: Overview of sign language tasks: Recognition (SLR), Translation (SLT), and Production (SLP), each with subtypes (e.g., isolated vs. continuous SLR; gloss- vs. gloss-free SLT), reflecting varied annotations and deployment needs.

While human interpreters can bridge this divide, limited availability, high cost, and scheduling constraints restrict access (Universal Translation Services, 2023), driving interest in automated sign language technologies as scalable alternatives in practice. Recent research spans three core tasks in sign language processing: recognition, translation, and production; yet progress remains constrained by fragmented datasets, inconsistent annotation, and limited cross-lingual coverage. In this survey, we address these challenges through a dataset-centric analysis focused on linguistic scope, annotation design, and task alignment. However, much of the literature relies on a small subset of benchmark datasets, overlooking many available resources. Prior surveys rarely conduct systematically dataset-level analyses of diversity, annotation granularity, or task suitability, obscuring the field's true coverage and hindering progress toward robust and inclusive sign language technologies.

Scope of Survey We survey 120 public sign language datasets spanning 35 languages for SLR, SLT, and SLP. We analyze data modalities, signer demographics, vocabulary size, and related metadata, revealing modality imbalance, annotation inconsistency, and limited generalizability. We further publicly release benchmark leaderboards and a 24-field *Sign-Language Datasheet*, together with a public GitHub repository, to enable transparent documentation and reproducible evaluation.

Table 1: Comparison of existing survey papers on sign language technology. "Perf. Eval." denotes whether the paper includes performance benchmarking. "Std. & Annot." indicates discussion of dataset standardization or annotation frameworks.

Survey Paper	Survey Category	Datasets Covered	Dataset Analysis	Challenge Analysis	Perf. Eval.	Std. & Annot.	Task Coverage
Alyami et al. 2024	SLR	17	✗	✗	✗	✗	Only SLR
Tao et al. 2024	SLR	24	✓	✗	✗	✗	Only SLR
Sarhan and Frintrop 2023	SLR	8	✓	✓	✗	✗	Only SLR
Minu et al. 2023	SLR	16	✗	✗	✗	✗	Only SLR
Madhiarasan and Roy 2022	SLR	34	✓	✓	✗	✗	Only SLR
Liang et al. 2023	SLT	15	✗	✓	✓	✗	Only SLT
Núñez-Marcos et al. 2023	SLT	33	✓	✓	✓	✗	Only SLT
Kumar Attar et al. 2023	SLT	22	✓	✓	✓	✗	Only SLT
Kahlon and Singh 2023	SLT	13	✗	✓	✗	✗	Only SLT
Rastgoo et al. 2024	SLP	9	✓	✓	✓	✗	Only SLP
Tan et al. 2024a	SLR, SLT, SLP	25	✓	✓	✓	✗	Partial
Papastratis et al. 2021	SLR, SLT, SLP	13	✓	✓	✓	✗	Partial
De Sisto et al. 2022	SLR, SLT	13	✓	✓	✓	✓	No Task Focus
Ours	**SLR, SLT, SLP**	**120**	✓	✓	✓	✓	**Complete**

Contributions (1) We present a unified and up-to-date survey of 120 datasets covering 35 sign languages and three core tasks: SLR, SLT, and SLP. (2) We systematically characterize persistent dataset-level challenges, including modality imbalance, signer bias, and annotation inconsistency. (3) We introduce practical guidelines for future dataset construction, outlining essential contents, recommended tools, and documentation standards. (4) We release harmonized benchmark leaderboards across tasks and datasets to enable reproducible evaluation and fair comparison.

2 Background

We review the linguistic foundations, task taxonomy, and historical evolution of sign language processing to contextualize dataset-centric analysis and benchmarking in later sections.

Linguistic Foundations Sign languages are natural visual–gestural languages comprising two channels: (i) *manual* (handshape, location, movement, orientation) and (ii) *non-manual* (facial expressions, mouthing, gaze, posture) (Boyes-Braem and Sutton-Spence, 2001). These asynchronous, multimodal signals challenge conventional sequential modeling paradigms. As most sign languages lack standardized orthographies, datasets rely on proxy intermediate representations, most commonly *glosses*, which map signs to approximate spoken-language words. A smaller subset of datasets adopts phonological encodings (e.g., HamNoSys), capturing fine-grained articulatory structure at substantial annotation cost. Together, these linguistic and representational constraints shape task formulation and evaluation.

Task Taxonomy Sign language processing spans three core tasks, each with variants that shape dataset design, annotation schemes, and modeling strategies (see Figure 1): (1) **Sign Language Recognition (SLR)** predicts gloss sequences from video. It includes *isolated* SLR (Laines et al., 2023; Vázquez-Enríquez et al., 2021), where each video contains a single sign, and *continuous* SLR (Gan et al., 2024a; Zhou et al., 2021c), which transcribes unsegmented sign streams. (2) **Sign Language Translation (SLT)** maps sign videos to spoken-language text. Early work relied on gloss-based pipelines (Camgoz et al., 2020; Fu et al., 2023; Yin and Read, 2020); more recent approaches adopt gloss-free formulations (Gong et al., 2024; Guan et al., 2024; Hu et al., 2023; Chen et al., 2022b) that enable direct video-to-text mapping. (3) **Sign Language Production (SLP)** synthesizes sign videos from text or gloss input, via retrieval-based methods (Saunders et al., 2020b), keypoint-based generation (Qi et al., 2024), or full-frame video synthesis (Zuo et al., 2025; Yin et al., 2024).

Task Evolution & Research Trends Research has progressed from finger-spelling and isolated sign recognition (Dreuw et al., 2007; Zhou et al., 2021c) to sentence-level translation and full video synthesis. However, progress remains concentrated on a small set of high-resource languages, notably ASL, BSL, CSL, and DGS, leaving many sign languages underrepresented. SLR has evolved toward continuous settings, introducing challenges such as coarticulation and temporal ambiguity (Hu et al., 2023; Gan et al., 2024a). SLT has shifted from gloss-based pipelines to end-to-end architectures, despite persistent data scarcity. SLP has transitioned from retrieval-based systems to generative models with signer-aware outputs (Saunders et al., 2022). Despite these advances, prior surveys often focus on individual tasks and provide limited analysis of dataset coverage, annotation granularity, or evaluation standards (Table 1). By contrast, we present a unified review of 120 datasets across SLR, SLT, and SLP, offering systematic insights

Table 2: Concise overview of representative *fingerspelling* datasets. Abbreviations: ASL—American SL; ArSL—Arabic SL; AzSL—Azerbaijani SL; ISL— Irish SL. For the complete list, please refer to our GitHub.

Dataset	Year	Language	#Signs	#Samples	#Signers	Domain
ChicagoFSWild (Shi et al., 2018)	2018	ASL	31	7,304 seq.	168	Letters, Chars.
ASL Digits (Mavi, 2020)	2020	ASL	10	21,800 img.	218	Letters
ArASL (Latif et al., 2019)	2019	ArSL	32	54,049 img.	40	Letters
AzSLD Fingerspelling (Alishzade and Hasanov, 2025)	2023	AzSL	32	10,864 img., 3,587 vid.	43	Letters
ISL-HS (Oliveira et al., 2017)	2017	ISL	23	468 vid., 58,114 img.	6	Letters

Table 3: Representative *isolated* sign-language datasets. Abbreviations: ASL—American SL; LSFB—Belgian French SL; CSL—Chinese SL; Auslan—Australian SL; LSA—Argentinian SL; TSL—Turkish SL. The full list is available on GitHub.

Dataset	Year	Lang.	#Signs	Dur.	#Samples	#Signers	Domain
MS-ASL (Joze and Koller, 2018)	2018	ASL	1,000	∼25 h	25,513 vid.	222	General
WLASL (Li et al., 2020)	2019	ASL	2,000	∼14 h	21,083 vid.	119	General
ASL Citizen (Desai et al., 2024)	2023	ASL	2,731	—	83,399 vid.	52	General
LSFB-isol (Fink et al., 2021)	2021	LSFB	395	—	47,551 vid.	85	General
DEVISIGN (Chai et al., 2014)	2014	CSL	4,414	—	331,050 vid.	30	General
SLR500 (Huang et al., 2018a)	2018	CSL	500	—	125,000 vid.	50	General
NMFs-CSL (Hu et al., 2021)	2020	CSL	1,067	—	32,010 vid.	10	General
MM-WLAuslan (Shen et al., 2024a)	2024	Auslan	3,215	∼2,500 h	282,900 vid.	73	General
LSA-64 (Ronchetti et al., 2023)	2016	LSA	64	—	3,200 vid.	10	Dictionary
BosphorusSign22k (Özdemir et al., 2020)	2020	TSL	744	∼19 h	22,542 vid.	6	Health/Finance
AUTSL (Sincan and Keles, 2020)	2020	TSL	226	21 h	38,336 samples	43	General

into modality, annotation depth, linguistic diversity, and task alignment. Collectively, these trends highlight the need for inclusive and well-documented datasets, which we address through a comprehensive analysis of datasets (Section 3), benchmark aggregation (Section 4), and best-practice guidelines for dataset development (Section 5,6).

3 Dataset Compendium

High-quality sign-language datasets are essential for training robust models in recognition, translation, and production. We organize existing datasets into three principal categories: (i) *Fingerspelling* datasets, capturing static images or short video clips of manual alphabets; (ii) *Isolated Sign Language Datasets (ISLD)*, in which individual signs are recorded as separate video samples; and (iii) *Continuous Sign Language Datasets (CSLD)*, comprising longer, connected sign sequences. Representative datasets are summarized in Tables 2, 3, and 4, with complete listings and extended metadata available in our GitHub repository.

Fingerspelling Datasets Table 2 summarizes representative fingerspelling datasets across diverse sign languages, ranging from early, small-scale laboratory benchmarks (e.g., *ASL Digits* (Mavi, 2020), *ArASL* (Latif et al., 2019)) to more recent in-the-wild corpora such as *ChicagoFSWild* (Shi et al., 2018) and *AzSLD Fingerspelling* (Alishzade and Hasanov, 2025). Early datasets offer controlled acquisition settings but limited variation in lighting, background, signer demographics, and handshape complexity. Recent datasets prioritize demographic diversity, higher spatial resolution, and heterogeneous recording conditions, supporting the development of more robust recognition models. Coverage of larger manual alphabets, including diacritics (e.g., AzSLD (Alishzade and Hasanov, 2025)), further facilitates cross-lingual transfer and adaptation across sign languages overall.

Isolated Sign Language Datasets Table 3 summarizes representative isolated sign language datasets for single-sign recognition. Foundational benchmarks such as *MS-ASL* (Joze and Koller, 2018) and *WLASL* (Li et al., 2020) introduced medium-to-large vocabularies (∼1k–2k signs) and remain widely adopted owing to their signer diversity and task generality. Subsequent datasets further expand vocabulary scale and linguistic coverage: *DEVISIGN* (Chai et al., 2014) contributes over 300k Chinese Sign Language samples, while *MM-WLAuslan* (Shen et al., 2024a) provides multi-view Auslan recordings that capture richer signer variation. Beyond raw video, recent datasets increasingly integrate crowd-sourced data and multimodal signals (e.g., RGB, depth, and skeleton) to better capture fine-grained signing behavior. Collectively, these increasingly realistic and diverse datasets underpin progress in signer-independent learning, large-vocabulary classification, and multimodal alignment overall substantially.

Continuous Sign Language Datasets Compared

Table 4: Representative *continuous* sign-language corpora. Abbreviations: ASL—American SL; BSL—British SL; CSL—Chinese SL; DGS—German SL; Auslan—Australian SL; LSA—Argentinian SL. The full list is available in GitHub repo.

Corpus	Year	Lang.	#Vocab	Dur.	#Samples	#Signers	Domain
RWTH-Boston-104 (Dreuw et al., 2007)	2007	ASL	104	8.7 min	201 sents.	3	General
How2Sign (Duarte et al., 2021)	2020	ASL	16k	79 h	36,783 sents.	11	General
OpenASL (Shi et al., 2022)	2022	ASL	33k	288 h	—	∼220	General
YouTube-ASL (Uthus et al., 2024)	2023	ASL	60k	∼1,000 h	—	>2,500	General
DailyMoth-70 h (Rust et al., 2024)	2024	ASL	19,694	75.8 h	48,386 clips	1	News
BSL-1K (Albanie et al., 2020)	2020	BSL	1,064	∼1,000 h	273,000 sents.	40	General
BOBSL (Albanie et al., 2021)	2021	BSL	2,281	1,467 h	1.2M seq.	39	General
CSL-Daily (Zhou et al., 2021a)	2021	CSL	2,000	—	20,645 vid.	10	General
RWTH-PHOENIX14T (Camgoz et al., 2018)	2020	DGS	2,887	∼10.5 h	8,257 sents.	9	Weather
Auslan-Daily Comm. (Shen et al., 2024b)	2024	Auslan	3,064	—	14,041 sents.	49	Daily
PHOENIX-News (Yin et al., 2024)	2024	DGS	190k	486 h	—	11	News
LSA-T (Dal Bianco et al., 2022)	2022	LSA-ES	14,239	21.8 h	14,880 sents.	103	General

Table 5: Annotation layers included in today's most-used continuous sign language corpora. A ✓ indicates the layer is provided; a ✗ means it is absent. "Multimodal" refers to any additional stream beyond RGB video (e.g., depth, pose skeleton, 3D mesh). A complete inventory of corpora and their metadata is available in our GitHub repository.

Corpus	Lang.	Video	Clip ID	Gloss	Sent. Align.	Multimodal	File Format
PHOENIX14T (Camgoz et al., 2018)	DGS	✓	✓	✓	✓	✓	CSV
CSL-Daily (Zhou et al., 2021a)	CSL	✓	✓	✓	✓	✓	TXT
How2Sign (Duarte et al., 2021)	ASL	✓	✓	✗	✓	✓	CSV
YouTube-ASL (Uthus et al., 2024)	ASL	✗	✓	✗	✓	✗	TXT
OpenASL (Shi et al., 2022)	Multi	✗	✓	✓	✓	✗	TSV

to isolated datasets, Continuous Sign Language Datasets (CSLDs) feature longer, discourse-level signing sequences. Early examples such as *RWTH-Boston-104* (Dreuw et al., 2007) contained limited annotated material, while more recent corpora such as *How2Sign* (Duarte et al., 2021) and *YouTube-ASL* (Uthus et al., 2024) scale to hundreds of hours and tens of thousands of unique signs. These large-scale datasets enable research on continuous sign language recognition (CSLR), translation (SLT), and sign language production (SLP). Modern CSLDs increasingly provide rich, multi-level annotations (e.g., glosses and sentence alignments), enabling linguistic analyses of coarticulation, sign boundaries, and domain-specific expressions. They support the study of spontaneous signing styles, non-manual cues such as facial expressions, and domain variation (e.g., news and conversation). Effectively leveraging such corpora requires addressing challenges in temporal alignment, segmentation, and multimodal integration.

4 Benchmarks & Leaderboards

Building on the datasets introduced in Section 3, we conduct a systematic benchmark analysis across sign language recognition, translation, and production. This section compares the performance of representative models on five widely used benchmark datasets: PHOENIX14T, CSL-Daily, How2Sign, YouTube-ASL, and OpenASL. The results are reported by task (SLR, SLT, and SLP) and stratified into gloss-based and gloss-free settings.

Recognition Benchmarks (SLR) Table 7 reports WER performance across recent models on PHOENIX14T and CSL-Daily. PHOENIX14T yields lower error rates overall, with Sign-VTCL (Chen et al., 2024a) achieving 17.9%. This advantage can be attributed to a clean annotation pipeline, a narrow topical focus (weather domain), and limited signer variation, which collectively promote stable motion-to-text alignment and favor evaluation under controlled conditions. In contrast, CSL-Daily presents consistently higher WERs (lowest 24.1%) despite using similar model architectures, reflecting substantially greater diversity in signers, topics, and recording environments. It includes casual daily expressions and rich multimodal inputs (RGB, depth, and skeleton), which enhance ecological validity at the cost of increased learning complexity. Accordingly, models exhibit larger performance gaps on CSL-Daily than on PHOENIX14T, underscoring its utility for benchmarking generalization. As sign language systems progress toward real-world deployment, CSL-Daily serves as a more challenging and realistic testbed, particularly for assessing signer-

Table 6: **Positioning the flagship continuous-sign corpora.** "Tasks" = which benchmark(s) the field mainly uses the corpus for. Abbreviations: SLR–recognition, SLT–translation, SLP–production.

Corpus	Why you *do* want it	Why you *don't*	Tasks
PHOENIX14T (Camgoz et al., 2018)	– CC-BY; effortless download – Text-aligned glosses → easy SLT baselines	– Only ≈10 h train ⇒ over-fit risk – Weather broadcast domain ⇒ narrow vocab	SLR, SLT, SLP
CSL-Daily (Zhou et al., 2021a)	– 2k everyday signs (+ depth, skeleton) – Signer-independent split shipped	– NDA gate; lab footage ⇒ low background variety – Light gloss noise	SLR, SLT
How2Sign (Duarte et al., 2021)	– 79 h RGB + depth + 3-D mesh – 3-D avatar drives SLP research	– No manual gloss layer – 3 TB raw download ⇒ storage heavy	SLT, SLP
YouTube-ASL (Uthus et al., 2024)	– ≈1,000 h in-the-wild clips – Community can extend corpus on the fly	– Only YT IDs (link-rot, geo-blocks) – Heterogeneous quality; no pose/depth	SLT (large-scale pre-train)
OpenASL (Shi et al., 2022)	– Apache-2.0 TSV annotations – 33k open-domain vocab—rare for ASL	– Must crawl videos yourself – Mixed gloss standards; tooling scant	SLT (open-domain)

Table 7: **CSLR leaderboard performance** on PHOENIX14T and CSL-Daily. All numbers are word error rates (WER), where lower values indicate better recognition accuracy. Full dataset statistics and links are available at the GitHub repository.

PHOENIX14T			CSL-Daily		
Model	**WER ↓**	**Input**	**Model**	**WER ↓**	**Input**
SignVTCL (Chen et al., 2024a)	17.9%	RGB, Skeleton, Flow	SignVTCL (Chen et al., 2024a)	24.1%	RGB, Skeleton, Flow
Cross-Ling (Wei and Chen, 2023)	18.5%	RGB	MAM-FSD (Zhu et al., 2025)	24.5%	RGB
C^{2}ST (Zhang et al., 2023b)	18.9%	RGB	TwoStream-SLT (Chen et al., 2022b)	25.3%	RGB, Skeleton
MultiSignGraph (Gan et al., 2024b)	19.1%	RGB	C^{2}ST (Zhang et al., 2023b)	25.8%	RGB
TwoStream-SLT (Chen et al., 2022b)	19.3%	RGB, Skeleton	MultiSignGraph (Gan et al., 2024b)	26.4%	RGB

(a) CSL-Daily (b) PHOENIX14T (c) How2Sign

Figure 2: **Word clouds of translation outputs** from three major SLT datasets: CSL-Daily, PHOENIX14T, and How2Sign. The visualization highlights frequent words in target sentences, revealing domain-specific vocabulary distributions.

independence, coarticulation effects, and robustness under natural conditions.

Translation Benchmarks (SLT) We compare gloss-based and gloss-free SLT on PHOENIX14T, CSL-Daily, and How2Sign, which differ significantly in annotation structure, domain, and linguistic complexity, leading to distinct benchmarking characteristics overall. On today's BLEU-centric setups and high-resource corpora, systems with intermediate gloss supervision often report higher scores; however, this largely reflects supervision availability, domain cleanliness, and metric choice rather than an intrinsic superiority of gloss-informed pipelines. By contrast, gloss-free approaches reduce annotation cost and scale more readily, particularly for languages without standardized gloss conventions in practice.

Gloss-based SLT Table 8 reports BLEU scores for models trained with intermediate gloss supervision. PHOENIX14T consistently yields higher performance, with TextCTC-SLT (Tan et al., 2024b) achieving 28.42% BLEU. Its narrow domain and well-aligned gloss–sentence pairs facilitate learning structured mappings. CSL-Daily, in contrast, spans more diverse everyday topics and exhibits greater signer variability. As a result, its BLEU scores are generally lower (max 25.8%), but it serves as a more realistic and challenging benchmark for evaluating semantic generalization.

Gloss-free SLT Table 9 benchmarks end-to-end models that translate videos directly into spoken language without gloss supervision. While gloss-free methods typically underperform gloss-based counterparts in BLEU, they offer increased scalability and significantly lower annotation cost. Among the datasets, PHOENIX14T and CSL-Daily remain dominant choices for gloss-free benchmarks. Although How2Sign yields lower BLEU scores (best: 15.5%), its large vocabulary, multi-camera recordings, and lack of gloss annotations make it a critical benchmark for real-world, large-scale SLT. Overall, the performance gap between gloss-based and gloss-free systems has narrowed substantially, shifting research attention increasingly toward multimodal pretraining and scaling strategies.

Production Benchmarks (SLP) We evaluate sign language production (SLP) models that generate sign videos from either gloss inputs (Gloss-to-Pose) or spoken-language text (Text-to-Pose). Table 10 reports BLEU scores for both settings. Prior SLP

Table 8: **Gloss-based SLT leaderboard** on PHOENIX14T and CSL-Daily. BLEU scores are reported on the test set; higher values indicate better translation performance. Full dataset statistics and links are available at the GitHub repository.

PHOENIX14T			**CSL-Daily**		
Model	**BLEU ↑**	**Input**	**Model**	**BLEU ↑**	**Input**
TextCTC-SLT (Tan et al., 2024b)	28.42%	RGB	TwoStream-SLT (Chen et al., 2022b)	25.79%	RGB, Skeleton
TwoStream-SLT (Chen et al., 2022b)	26.71%	RGB, Skeleton	SLTUNET (Zhang et al., 2023a)	23.76%	RGB
SLTUNET (Zhang et al., 2023a)	26.00%	RGB	TextCTC-SLT (Tan et al., 2024b)	22.47%	RGB
ConSLT (Fu et al., 2023)	25.48%	RGB	MMTLB (Chen et al., 2022a)	21.46%	RGB
MMTLB (Chen et al., 2022a)	24.60%	RGB	BN-TIN-Transf + BT (Zhou et al., 2021b)	19.67%	RGB

Table 9: **Gloss-free SLT leaderboard** on PHOENIX14T, CSL-Daily, and How2Sign. BLEU scores are reported on the test set; higher values indicate better translation performance. Full leaderboard details and links are available at the GitHub repository.

PHOENIX14T		**CSL-Daily**		**How2Sign**	
Model	**BLEU ↑**	**Model**	**BLEU ↑**	**Model**	**BLEU ↑**
CV-SLT (Zhao et al., 2024)	29.27%	Uni-Sign (Li et al., 2025)	26.36%	SSVP-SLT(Rust et al., 2024)	15.5%
MSKA-SLT (Guan et al., 2024)	29.03%	MSKA-SLT (Guan et al., 2024)	25.52%	Uni-Sign (Li et al., 2025)	14.9%
TwoStream-SLT (Chen et al., 2022b)	28.95%	TwoStream-SLT (Chen et al., 2022b)	25.42%	SignMusketeers(Gueuwou et al., 2025)	14.3%
SLTUNET (Zhang et al., 2023a)	28.47%	SLTUNET (Zhang et al., 2023a)	25.01%	VAP (Jiao et al., 2024)	12.87%
MMTLB (Chen et al., 2022a)	28.39%	MMTLB (Chen et al., 2022a)	23.92%	SLT-CC (Jang et al., 2025)	12.70%
IP-SLT (Yao et al., 2023)	27.97%	C^2ST (Zhang et al., 2023b)	21.61%	YouTube-ASL (Uthus et al., 2024)	12.39%
C^2RL (Zhang et al., 2023b)	26.75%	XmDA (Ye et al., 2023)	21.58%	SLT-SEM (Hamidullah et al., 2024)	11.70%
VAP (Jiao et al., 2024)	26.16%	BN-TIN-Transf + BT (Zhou et al., 2021b)	21.34%	FLa-LLM (Chen et al., 2024b)	9.66%

work lacks standardized pipelines for pose extraction, 3D lifting, and evaluation, and many models are not open-sourced, limiting reproducibility. Consequently, discrepancies arise when retraining public models or comparing results across studies; our analysis therefore relies on reported leaderboard results. Among Gloss-to-Pose models, FS-NET (Saunders et al., 2022) achieves the highest score (18.78%), benefiting from alignment-aware supervision. For Text-to-Pose, Spoken2Sign (Zuo et al., 2024) attains the best performance (25.46%), despite the more complex input space, highlighting the effectiveness of large-scale text encoders. Other strong models such as SignDiff (Fang et al., 2023) and SignGen (Qi et al., 2024) employ diffusion-based generative modeling to improve visual realism. Observed BLEU gaps in SLP largely reflect evaluation protocols and dataset curation rather than an inherent advantage of gloss conditioning. Gloss-free text-to-pose systems reduce annotation cost and remain appealing for low-resource settings, with performance gaps narrowing under multimodal conditioning and large-scale pretraining.

Text-only SLP Gloss-free systems such as SignDiff and SignGen achieve competitive BLEU scores without intermediate gloss annotations. Spoken2Sign remains the top-performing model, suggesting that strong textual pretraining can compensate for the absence of explicit gloss structure. Models including T2S-GPT (Yin et al., 2024) and NSLP-G (+fine-tuning) (Hwang et al., 2021) further illustrate the benefits of fine-tuning, though they still trail the strongest methods. Overall, the field is shifting toward direct Text-to-Pose modeling, which is more scalable and annotation-efficient, while maintaining fidelity and temporal smoothness remains an open challenge.

Future Evaluation for SLP SLP remains a relatively new task with fewer public works, and evaluations are still concentrated on PHOENIX-2014T and How2Sign. To retain comparability, we report BLEU when back-translation is used, but its reliability is fundamentally constrained by the underlying SLT model. Several How2Sign evaluations depend on pre-trained back-translators whose training details are undisclosed, leading to substantial variation in reported scores. Thus, BLEU should be interpreted primarily as a relative (rather than absolute) indicator of generation quality. To provide a more complete assessment of intelligibility and deployability, we recommend complementing BLEU with $\mathrm{MPJPE}_{\mathrm{DTW}}$, Hand-MJE, timing F1, and human ratings. For reproducibility, evaluations should also **explicitly** specify input modality (RGB / pose / fusion), supervision type (gloss-conditioned / text-to-pose), use of large-scale pretraining, and sampling rate (fps). This protocol is compatible with existing benchmarks and enables more consistent cross-paper comparisons.

5 Dataset Challenges

Despite rapid progress in sign language modeling, several structural challenges persist in accessibility, linguistic coverage, annotation standardization, and ecological validity. This section identifies five key issues grounded in the visualizations and bench-

Table 10: **SLP leaderboard** for **Gloss-to-Pose** and **Text-to-Pose** models. BLEU scores are reported on the test set; higher values indicate better video generation performance. Full dataset details and links are available at the GitHub repository.

Gloss-to-Pose		Text-to-Pose		
Model	**BLEU ↑**	**Model**	**BLEU ↑**	**Gloss-Free**
FS-NET (Saunders et al., 2022)	18.78%	Spoken2Sign (Zuo et al., 2024)	25.46%	No
Adversarial Training (Saunders et al., 2020a)	11.70%	SignDiff (Fang et al., 2023)	22.15%	Yes
Progressive Transf (Saunders et al., 2020c)	10.43%	FS-NET (Saunders et al., 2022)	21.10%	Yes
NSLP-G (Hwang et al., 2021)	9.39%	SignGen (Qi et al., 2024)	19.71%	Yes
LVMCN (Wang et al., 2024)	9.36%	T2S-GPT (Yin et al., 2024)	11.87%	Yes
Data-Driven (Walsh et al., 2024)	9.17%	NSLP-G (+ Fine-tuning) (Hwang et al., 2021)	11.07%	Yes

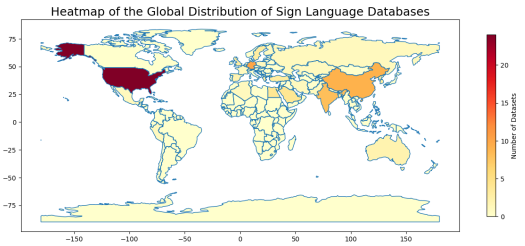


Figure 3: **Geographic distribution of sign language datasets.** The heatmap highlights the number of datasets collected per country or region. Darker colors indicate higher dataset density, with most resources concentrated in Europe, North America, and East Asia. [Best zooming in to view].

mark analyses presented earlier. Although we sought to quantify factors such as inter-annotator agreement (IAA), demographic diversity, and ecological validity, our audit indicates that these attributes are seldom reported in public corpora. Accordingly, we treat these documentation gaps as limitations rather than imputing missing values.

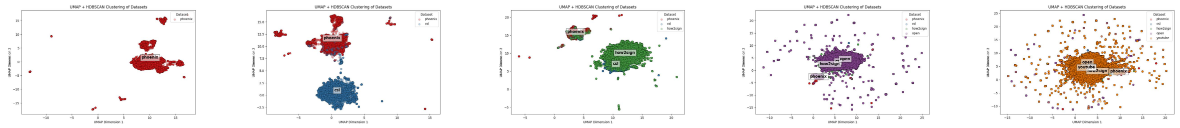
Access Barriers & Sustainability Although over 100 sign language datasets have been released, only a limited subset is widely adopted. As shown in Table 5 and Table 6, corpora such as CSL-Daily and BOBSL require data agreements or institutional approval, restricting their use in open-source research. Older datasets including SIGNUM (von Agris and Kraiss, 2010) suffer from link rot and are no longer accessible. Datasets such as YouTube-ASL provide only video identifiers, making reproducibility fragile and long-term access unreliable. In contrast, PHOENIX14T remains widely used due to its open access, clean gloss alignment, and consistent CSV format, despite its limited scale.

Linguistic & Geographic Imbalance Figure 3 indicates that most public corpora concentrate on a small number of high-resource sign languages (e.g., ASL, DGS, CSL, ISL), while many others, particularly sign languages in South Asia, Africa, and Indigenous or village communities, remain unrepresented. Even within a single language, regional variation is rarely documented. High-resource languages benefit from large, richly annotated corpora (e.g., YouTube-ASL), whereas underrepresented languages often rely on small, lab-collected datasets with sparse metadata or restricted access, leading to a compounding advantage. Figure 4 further shows that sentence embeddings from different datasets (PHOENIX14T, CSL-Daily, How2Sign, OpenASL, YouTube-ASL) form largely disjoint clusters, reflecting poor semantic alignment across domains and hindering multi-dataset pretraining and zero-shot transfer.

Inconsistent Modalities & Annotations Sign language datasets vary widely in input modality (RGB, depth, pose), data format (CSV, TSV, JSON), and annotation layers (e.g., glosses, sentence alignment). Table 5 shows that only PHOENIX14T and CSL-Daily provide relatively complete supervision, whereas OpenASL and YouTube-ASL lack glosses or synchronized modalities. Such heterogeneity complicates joint modeling and undermines reproducibility. Moreover, even within datasets, annotation conventions differ: for example, translation fields are labeled `translation` in PHOENIX14T but `SENTENCE` in How2Sign. These inconsistencies increase preprocessing overhead and impede cross-dataset generalization, underscoring the need for harmonized data formats and annotation schemas.

Gloss Quality & Transferability Gloss annotations enhance recognition and translation but remain costly, labor-intensive, and inconsistent in the absence of standardized guidelines. Annotator variability, even within the same language such as across German Sign Language corpora, limits effective fine-tuning and cross-corpus transfer. Large-scale datasets such as How2Sign and YouTube-ASL omit glosses entirely, prioritizing scale over structured linguistic grounding. Although recent gloss-free approaches narrow the performance gap, gloss annotations remain valuable for interpretability and faster convergence in low-resource settings. However, inconsistent conventions weaken these benefits, underscoring the need for standardized glossing practices and broader coverage.

Semantic & Topical Divergence As demon-



(a) PHOENIX14T (b) + CSL-Daily (c) + How2Sign (d) + OpenASL (e) + YouTube-ASL

Figure 4: **UMAP projection of sentence embeddings across datasets.** Each panel incrementally adds one dataset to PHOENIX14T, illustrating how semantic domains expand and overlap in embedding space. Colors: PHOENIX14T (red), CSL-Daily (blue), How2Sign (green), OpenASL (purple), YouTube-ASL (orange). [Best zooming in to view].

strated in Figure 2, vocabulary distributions differ markedly across datasets. PHOENIX14T reflects weather forecasts, whereas How2Sign captures instructional content. Such domain differences influence SLT performance and model generalizability. Models trained on narrow-domain corpora often fail to generalize to broader topics without explicit adaptation. A more diverse collection of topic-balanced, gloss-annotated datasets is therefore critical for real-world deployment and zero-shot robustness. Targeted domain-adaptation methods that leverage semantic relationships between topics may further enhance cross-domain transfer.

6 Future Dataset Curation

To support scalable and high-quality sign language research, future datasets should prioritize linguistic coverage, ecological realism, multimodal alignment, and interoperable design. This section distills best practices derived from the challenges and empirical insights discussed earlier.

Video Selection & Preprocessing To ensure real-world relevance, video content should span diverse contexts, including greetings, healthcare, education, emergencies, daily life, and news. Sourcing from open tutorials or platforms such as YouTube promotes topical diversity; however, videos must be filtered to remove low-resolution or noisy segments, as fine-grained hand and facial cues are essential. Datasets should balance sentence length, domain coverage, and linguistic complexity, with long-form videos segmented at semantically coherent sign boundaries to remove idle frames. Transcriptions, whether human- or machine-generated, must be verified for temporal alignment and semantic accuracy. To mitigate geographic and dialect bias, we recommend stratified sampling by region and dialect, drawing from multiple locales and enforcing minimum per-region quotas.

Annotation Strategy A modular annotation strategy improves usability and extensibility. At minimum, each video should include a unique identifier and a cleaned sentence-level translation, with additional layers released incrementally. Gloss annotations provide interpretable intermediates for CSLR and SLT but require expert annotators and are best introduced in later phases. Temporal sign boundaries, defined by start and end timestamps for each gloss unit, support segmentation and timing-aware generation. Skeleton-based pose representations are lightweight yet effective across recognition and production, while non-manual cues can be modeled using Facial Action Units (FAUs). FAUs, derived from the Facial Action Coding System (FACS), encode facial muscle activations with grammatical and affective functions in signed languages (Ekman et al., 2002; Zeshan, 2004). They provide a standardized interface and can be extracted using established toolkits such as OpenFace (Baltrusaitis et al., 2018). This layered strategy enables early data release and later enrichment.

Annotation Tool Selection Several tools support sign language annotation. ELAN (Wittenburg et al., 2006) remains the most widely adopted due to its hierarchical annotation and multimodal support. Alternative tools such as SignStream and SLAN-tool offer specialized functionality, including linguistic transcription and semi-automated segmentation. For reference, we summarize their capabilities and limitations in a comparative table in the Appendix.

7 Conclusion

We survey 120 sign-language datasets spanning recognition, translation, and production, summarizing challenges such as uneven geographic coverage, gloss inconsistency, modality imbalance, and fragmented benchmarks. By synthesizing leaderboards, comparative analyses, and semantic visualizations, we identify performance gaps and emphasize the importance of ecological diversity, reproducibility, and richer annotations. We also outline practical guidelines for dataset construction, annotation tooling, and standardized evaluation. By consolidating scattered resources and observations, this survey aims to inform more inclusive and linguistically grounded research in sign-language AI.

8 Limitations

While our survey offers the most extensive public index of sign-language datasets to date, it is nevertheless subject to six key constraints:

1. **Language imbalance.** Openly available corpora still concentrate on a handful of high-resource sign languages (ASL, DGS, CSL, BSL). Therefore, any conclusions about cross-lingual transferability may fail to generalize to historically under-represented communities—such as many African, Indigenous, and village sign languages—without further evidence.

2. **Metadata completeness.** Statistics such as signer counts were copied verbatim from the original papers or repository `README`s; we did not re-annotate every clip. Minor inaccuracies may thus persist despite our best cross-checks.

3. **Benchmark scope.** The quantitative leaderboards in Section 4 focus on five flagship, general-purpose datasets. Highly specialised domains (e.g., medical or legal signing) remain to be benchmarked in future work.

4. **Visualization bias.** All embedding maps rely on a single UMAP seed and default hyper-parameters. Alternative random seeds or dimensionality-reduction methods could expose slightly different cluster boundaries.

5. **Lack of human evaluation.** We did not yet conduct usability studies with Deaf signers to vet the proposed 24-field datasheet template; structured community feedback therefore remains an essential item on our agenda.

6. **Community vetting.** While the proposed 24-field datasheet template aims to standardize documentation, it has not yet been reviewed by Deaf communities or signers, which we consider a key limitation. To address this, we will run an open call for feedback and provide a public GitHub issue template to collect comments; we will summarize and integrate the input in the next iteration and document changes in a public changelog. However, achieving complete and comprehensive validation is challenging: our survey spans 35 sign languages, so participation and collaboration from Deaf communities across these language varieties is essential to make this effort as thorough as possible.

Broader Impact & Ethical Considerations

Potential benefits. By unifying dispersed resources and releasing a standardized datasheet template, we lower entry barriers for newcomers, foster reproducibility, and expose low-resource gaps that merit targeted investment.

Risks and mitigations. Responsible development of our approach requires careful consideration of potential negative impacts.

- *Signer privacy.* Many videos display identifiable faces. We therefore urge dataset curators to spell out licence terms and, where appropriate, add options for anonymisation (face-blurring, gated access). See Section 6.

- *Bias amplification.* Benchmarks dominated by white, Western signers can yield models that under-perform for minority communities. Figure 3 highlights this imbalance; we advocate community-led data collection to correct it.

- *Malicious use.* Synthetic sign-language output might enable deep-fake content. We recommend visible or invisible watermarks and disclosure when such footage is shared.

- *Environmental cost.* Our analyses used <1 GPU-hour (Appendix B). Still, future large-scale training should report carbon footprints and favour efficient architectures.

Responsible NLP Checklist (Filled)

For every item we answer *Yes/No* and cite a supporting section or justification.

A1 Limitations described? Yes — Section 8.

A2 Risks discussed? Yes — Section 8.

B1 Creators cited? Yes — see dataset/tool citations in Tables 1–7.

B2 Licence or terms specified? Yes — "Available" column plus Section 3.

B3 Intended use respected? Yes — we never repurpose data beyond stated research scopes (Section 3).

B4 PII/offensive content handled? Yes — exclusion criteria detailed in Section 3; privacy safeguards in Section 8.

B5 Documentation supplied? Yes — 24-field datasheet template (Appendix A and GitHub).

B6 Statistics reported? Yes — sample counts, signer numbers, and splits are listed for every dataset table.

C1 Compute budget recorded? Yes — under one GPU-hour for all UMAP runs (Appendix B).

C2 Experimental hyper-parameters? N/A — survey only; no model training conducted.

C3 Error bars or variance? N/A — we quote numbers exactly as reported by original papers.

C4 Package versions noted? Yes — UMAP 0.5.6, scikit-learn 1.5.0 (Appendix B).

D1 Annotator instructions shared? N/A — no fresh data collection.

D2 Recruitment or payment details? N/A.

D3 Consent procedures stated? N/A.

D4 IRB approval mentioned? N/A — public datasets presumed compliant.

D5 Annotator demographics supplied? N/A.

E1 AI assistants used? Yes — all writing and analysis were performed manually by the authors. We only use AI assistants for Editing (e.g., grammar, spelling, word choice).

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A Appendix

This appendix provides supplementary material, including a detailed comparison of annotation tools and comprehensive tables covering the sign language datasets surveyed in this work.

Annotation Tools Details. The choice of annotation tools is critical for dataset sustainability, reproducibility, and long-term usability. As discussed in Section 6, several annotation tools are commonly used in sign language research:

- **ELAN** (Wittenburg et al., 2006) ELAN is the most stable and widely adopted annotation platform for sign language corpora. It supports hierarchical tier structures, for example separating gloss annotations from sentence-level translations, and synchronized multimodal streams, including video, audio, and waveform data. Its XML-based storage format facilitates long-term readability and interoperability, making ELAN the preferred choice for large-scale and longitudinal dataset development.

- **More Tools** SignStream (Neidle et al., 2001) is optimized for fine-grained linguistic transcription of visual–gestural data but offers limited interoperability outside research communities. SLAN-tool (Mukushev et al., 2022) integrates semi-automated neural segmentation to accelerate annotation workflows. However, it depends on ELAN for broader compatibility and may face availability or maintenance constraints.

Annotation Tool Comparison. Table 11 compares three widely used sign language annotation tools, namely SignStream, ELAN, and SLAN-tool, across dimensions including functionality, usability, interoperability, and modality support within typical sign language research pipelines.

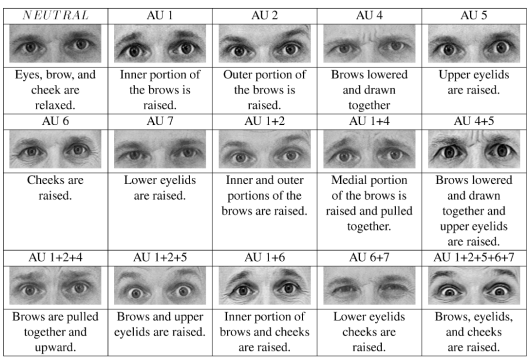

Figure 5: Upper facial Action Units and co-activation patterns. Image adapted from (Tian et al., 2001).

Facial Action Units (FAUs). The Facial Action Coding System (FACS) provides an anatomically grounded and fine-grained representation of facial expressions by decomposing them into Action Units (AUs), each corresponding to the activation of a specific facial muscle or muscle group. Unlike holistic expression labels, FAUs enable a compositional representation of non-manual signals that are critical to sign language phonology and grammar in practice. Examples include AU1, AU2, and AU4 for eyebrow movement, as well as AU12 for lip-corner activation (Ekman et al., 2002; Zeshan, 2004; McCullough and Emmorey, 2009). Figure 5 illustrates several upper facial Action Units, common co-activation patterns, and the facial expressions they convey.

Dataset Tables. Tables 13–19 provide a comprehensive overview of the 120 datasets surveyed in this work. The tables are organized by dataset type, including fingerspelling, isolated, and continuous datasets, and summarize key metadata such as sign language, vocabulary size, number of signers, recording modalities, domain coverage, benchmark usage, and evaluation settings across tasks.

However, finer-grained attributes, such as inter-annotator agreement (IAA), annotation guidelines, signer demographics, and recording or collection conditions, are often inconsistently or incompletely reported in the original literature, as discussed in Section 5. To assess transparency, we conduct a dedicated analysis of reporting completeness across both isolated and continuous sign language datasets. Table 12 summarizes the extent to which these attributes are explicitly documented in the source publications. Following a conservative assessment strategy based solely on information explicitly stated in the papers, each attribute is categorized as Covered, Partially Covered, Not Covered, or Unknown. Percentages are computed separately over the 54 isolated datasets and the 34 continuous sign language datasets. This analysis focuses on reporting completeness rather than re-evaluating annotation quality or demographic distributions, which are largely unavailable or inconsistently documented in existing sources.

Additional Visualizations. Figure 4 presents UMAP projections of sentence-level embeddings for five representative datasets. High-resolution figures and embedding files are archived in the accompanying GitHub repository and are publicly available for further inspection and reuse.

Table 11: Comparison of sign language annotation tools across functionality, usability, and integration.

Aspect	SignStream	ELAN	SLAN-tool
Motivation	Linguistic transcription of visual-gestural languages.	Multimodal annotation of natural communication.	AI-assisted annotation for sign language NLP.
Advantages	• Multilevel synchronization • Linguistically detailed annotations	• Tier-based structure • Flexible format support • Widely adopted	• Neural segmentation • Semi-automatic annotation • ELAN-compatible
Disadvantages	• Requires expert knowledge • Limited toolchain integration	• Steep learning curve • Requires schema familiarity	• Dependent on ELAN • Performance tied to pretrained models
Data Format	Visual-gestural input only; low interoperability	Broad audio/video/text support; exportable	Optimized for segmentation; integrates with ELAN
Ease of Use	Researcher-friendly for sign linguists	Feature-rich but may require training	Customizable GUI for targeted workflows
Unique Features	Multilevel annotation for both signed and spoken input	Timestamped, hierarchical annotation tiers	Neural integration for active signing segmentation

Table 12: Reporting completeness statistics for isolated and continuous sign language datasets.

Attribute	**Isolated (%)**				**Continuous (%)**			
	Cov.	**Part.**	**Not**	**Unk.**	**Cov.**	**Part.**	**Not**	**Unk.**
Inter-Annotator Agreement (IAA)	5.6	3.7	79.6	11.1	0.0	8.8	82.4	8.8
Annotation Guidelines	7.4	37.0	44.4	11.1	5.9	61.8	23.5	8.8
Signer Demographics	18.5	57.4	13.0	11.1	26.5	47.1	17.6	8.8
Recording / Collection Conditions	66.7	22.2	0.0	11.1	67.6	20.6	2.9	8.8

Cov. indicates that the attribute is explicitly and clearly documented in the original paper; **Part.** indicates that the attribute is mentioned but lacks sufficient detail or completeness; **Not** indicates that the attribute is not reported at all; **Unk.** indicates that the attribute cannot be reliably determined due to missing or inaccessible information.

Table 13: FingerSpelling Sign Language Datasets

Dataset	**Year**	**Language**	**Vocab. Size**	**#Samples**	**#Signers**	**Domain**	**Collection Source**	**Resolution**	**Modality**	**Publication**	**Available**	**Task**	**Baseline Model Accuracy**
ChicagoFSWild (Shi et al., 2018)	2018	American	31	7,304 sequences	168	Letters + Char	Online	640×360	RGB	American Sign Language fingerspelling recognition in the wild	✓	SLR	–
ChicagoFSWild+ (Shi et al., 2019)	2019	American	–	55,232 sequences	260	Letters + Char	Online	–	RGB	Fingerspelling recognition in the wild with iterative visual attention	✓	SLR	–
ASL Digits (Mavi, 2020)	2020	American	10	21,800 images	218	Letters	Camera	3024×3024	RGB	A New Dataset and Proposed Convolutional Neural Network Architecture for Classification of American Sign Language Digits	✓	SLR	–
27 Class ASL (Mavi and Dikle, 2022)	2022	American	27	130 images	173	Letters	Camera	3024×3024	RGB	A New 27 Class Sign Language Dataset Collected from 173 Individuals	✓	SLR	–
FSboard (Georg et al., 2025)	2023	American	∼3.2M characters	151,000 samples	147	Letters	Mobile camera	1944 × 2592	RGB Video → Landmark (pose/hand)	FSboard: Over 3 million characters of ASL fingerspelling collected via smartphones	✓	SLR	11.1% CER (52.9% Top-1 Accuracy, ByT5-small baseline) (Georg et al., 2025)
ArASL (Latif et al., 2019)	2019	Arabic	32	54,049 images	40	Letters	Mobile camera	64×64	RGB	ArASL: Arabic Alphabets Sign Language Dataset	✓	SLR	–
RGB AASL (Al-Barham et al., 2023)	2023	Arabic	31	7,857 images	200	Letters	Camera	–	RGB	RGB Arabic Alphabets Sign Language Dataset	✓	SLR	–
AzSLD Fingerspelling (Alishzade and Hasanov, 2025)	2023	Azerbaijani	32	10,864 images, 3,587 videos	43	Letters + Gesture	Telegram	–	RGB	AzSLD: Azerbaijani Sign Language Dataset for Fingerspelling, Word, and Sentence Translation with Baseline Software	✓	SLR	–
ISL-HS (Oliveira et al., 2017)	2017	Irish	23	468 videos, 58,114 images	6	Letters	Mobile camera	640×480	RGB	A Dataset for Irish Sign Language Recognition	✓	SLR	95% Accuracy (Oliveira et al., 2017)
RWTH-FingerSpelling (Dreuw et al., 2006)	2006	Germany	35	1,400 image sequences	20	Letters + Umlauts + Number	Lab	320×240, 352×288	RGB	Modeling Image Variability in Appearance-Based Gesture Recognition	✓	SLR	35.7% Error Rate (Dreuw et al., 2006)

Table 14: Isolated Sign Language Dataset (Part I)

Dataset	Year	Language	Vocab. Size	Duration	#Samples	#Signers	Domain	Collection Source	Resolution	Modality	Publication	Available	Task	Baseline Model Accuracy
Alabib-65 (Khellas and Seghir, 2023)	2023	Algerian	65	–	6,328 videos	29	General	iPad Air	720×1,280, 1,080×1,920	RGB	Alabib-65: A Realistic Dataset for Algerian Sign Language Recognition	×	SLR	70.83% (Khellas and Seghir, 2023)
Purdue RVL-SLLL (Martínez et al., 2002)	2002	American	101+	–	2,576 video clips	14	Motion primitives + Handshapes + General	Lab	640×480	RGB	Purdue RVL-SLLL ASL Database for Automatic Recognition of American Sign Language	Contact Author	SLR	–
Boston ASLLVD (Athitsos et al., 2008)	2008	American	3,314	–	9,800 tokens	6	General	Lab	–	RGB	The American Sign Language Lexicon Video Dataset	Partially	SLR	–
MSR Gesture3D (Chen et al., 2017)	2017	American	12	–	336 sequences	10	Gesture	Lab	–	RGB-D	Action recognition from depth sequences using weighted fusion of 2D and 3D auto-correlation of gradients features	✓	SLR	–
MS-ASL (Joze and Koller, 2018)	2018	American	1,000	∼25 hours	25,513 videos	222	General	Lab	–	RGB	MS-ASL: A Large-Scale Data Set and Benchmark for Understanding American Sign Language	✓	SLR, SLP	–
WLASL (Li et al., 2020)	2019	American	2,000	∼14 hours	21,083 videos	119	General	Lab	–	RGB	Word-level Deep Sign Language Recognition from Video: A New Large-scale Dataset and Methods Comparison	✓	SLR, SLP	Top-10 66.31% (I3D) (Li et al., 2020)
ASL-100-RGBD (Hassan et al., 2020)	2020	American	100	–	∼4,150 tokens	22	General	Lab	1920×1080, 512×424	RGB, Skeleton, Depth and HDface	An Isolated-Signing RGBD Dataset of 100 ASL Signs Produced by Fluent ASL Signers	✓	SLR	-
ASL CrowdSourcing (Bragg et al., 2022)	2022	American	60	–	1,906 videos	29	General	Crowd	–	RGB	Exploring Collection of Sign Language Videos through Crowdsourcing	×	SLR	–
ASL-Skeleton3D (de Amorim and Zanchettin, 2022)	2022	American	–	–	9,747 samples	6	General	Lab	–	RGB	ASL-Skeleton3D and ASL-Phono: Two Novel Datasets for the American Sign Language	✓	SLR	–
ASL-Phono (de Amorim and Zanchettin, 2022)	2022	American	2,294	–	9,747 samples	6	Linguistics-based	Lab	–	RGB	ASL-Skeleton3D and ASL-Phono: Two Novel Datasets for the American Sign Language	✓	SLR	–
ASLLRP Sign Bank (Neidle et al., 2022)	2022	American	6,000	–	41,830 lexical signs	–	Lexical	Lab	–	RGB	ASL Video Corpora & Sign Bank: Resources Available through the American Sign Language Linguistic Research Project (ASLLRP)	✓	SLR	–
ASL Citizen (Desai et al., 2024)	2023	American	2,731	–	83,399 videos	52	General	Crowd	–	RGB	ASL Citizen: A Community-Sourced Dataset for Advancing Isolated Sign Language Recognition	✓	SLR	Top-10 90.86% (Desai et al., 2024)
PopSign ASL v1.0 (Starner et al., 2023)	2024	American	250	–	214,326 videos	47	General	Smartphone	–	RGB	PopSign ASL v1.0: An Isolated ASL Dataset Collected via Smartphones	Contact Author	SLR	83.80% (Starner et al., 2023)
ArSL corpus (Almohimeed et al., 2010)	2010	Arabic	710	–	203 sentences	–	General	Lab	640×480	RGB	An Arabic Sign Language corpus for instructional language in school	✓	SLR	–
SignsWorld Atlas (Shohieb et al., 2015)	2015	Arabic	∼500	–	–	10	General	Lab	–	RGB	SignsWorld Atlas; a benchmark Arabic Sign Language database	×	SLR	–
LSA-64 (Ronchetti et al., 2023)	2023	Argentina	64	–	3,200 video sequences	10	Dictionary	Lab	–	RGB	LSA64: An Argentinian Sign Language Dataset	✓	SLR	–
ArSLRS (Ibrahim et al., 2018)	2018	Arabic	30	–	450 videos	–	General	Lab	–	RGB	An Automatic Arabic Sign Language Recognition System (ArSLRS)	×	SLR	97% (Ibrahim et al., 2018)
ArSL for Deaf Drivers (Abbas et al., 2021)	2021	Arabic	215	–	215 videos	3	Driver	Lab	–	RGB	Towards an Arabic Sign Language (ArSL) corpus for deaf drivers	✓	SLR	10.23% WER (Abbas et al., 2021)

Table 15: Isolated Sign Language Dataset (Part II)

Dataset	Year	Language	Vocab. Size	Duration	#Samples	#Signers	Domain	Collection Source	Resolution	Modality	Publication	Available	Task	Baseline Model Accuracy
KArSL (Sidig et al., 2021)	2021	Arabic	502	–	75,300 samples	3	General	Lab	1920×1080, 512×424	RGB-D, Skeleton	KArSL: Arabic Sign Language Database	✓	SLR	–
MM-WLAuslan (Shen et al., 2024a)	2024	Australian	3,215	∼2,500 hours	282,900 videos	73	General	Lab	Varies	RGB-D, Pose data	MM-WLAuslan: Multi-View Multi-Modal Word-Level Australian Sign Language Recognition Dataset	✓	SLR	-
AzSLD Words (Alishzade and Hasanov, 2025)	2023	Azerbaijani	100	–	–	–	–	–	–	RGB	AzSLD: Azerbaijani Sign Language Dataset for Fingerspelling, Word & Sentence Translation with Baseline Software	✓	SLR	–
BDSL 49 (Hasib et al., 2023)	2022	Bangla	49	–	29,490 images	14	General	Smartphone	–	RGB	BDSL 49: A Comprehensive Dataset of Bangla Sign Language	✓	SLR	–
MINDS-Libras	2019	Brazilian	20	–	1,200 videos	12	Gesture	Lab	1920×1080	RGB	(no publication title)	✓	SLR	–
BSLDICT (Momeni et al., 2020)	2020	British	9,283	–	14,210 videos	>28	Dictionary	Website	–	RGB	Watch, read and lookup: learning to spot signs from multiple supervisors	✓	SLR	–
DEVISIGN	2014	Chinese	4,414	–	331,050 vocabulary data	30	General	Lab	–	RGB-D, Skeleton	(no publication title)	Contact Author	SLR	–
CSLR-HMM-D1 (Zhang et al., 2016)	2016	Chinese	100	–	500 videos	1	General	Lab	–	RGB-D, Skeleton	CHINESE SIGN LANGUAGE RECOGNITION WITH ADAPTIVE HMM	×	SLR	–
CSLR-HMM-D2 (Zhang et al., 2016)	2016	Chinese	500	–	2,500 videos	1	General	Lab	–	RGB-D, Skeleton	CHINESE SIGN LANGUAGE RECOGNITION WITH ADAPTIVE HMM	×	SLR	–
SLR500 (Huang et al., 2018a)	2018	Chinese	500	–	125,000 videos	50	General	Lab	–	RGB-D, 3D Joints Information	Attention-Based 3D-CNNs for Large-Vocabulary Sign Language Recognition	Agreement Needed	SLR	53.8% (Huang et al., 2018a)
NMFs-CSL (Hu et al., 2021)	2020	Chinese	1,067	–	32,010 videos	10	General	Lab	–	RGB	Global-Local Enhancement Network for NMF-Aware Sign Language Recognition	Agreement Needed	SLR	Top-5 90.5% (Hu et al., 2021)
NCSL (Wang et al., 2022)	2022	Chinese	300	–	90,000 videos	30	General	Lab	–	RGB	(2+1)D-SLR: An Efficient Network for Video Sign Language Recognition	×	SLR	Top-1 96.4% (Wang et al., 2022)
DGS Kinect 20 (Cooper et al., 2012)	2012	Germany	20	–	840 samples	6	General	Lab	–	RGB	Sign Language Recognition Using Sub-Units	Contact Author	SLR	Top-1 76% (Cooper et al., 2012)
DGS Kinect 40 (Cooper et al., 2012)	2012	Germany	40	–	3,000 samples	15	General	Lab	–	RGB	Sign Language Recognition Using Sub-Units	Contact Author	SLR	–
DW-DGS (Langer et al., 2024)	2023	Germany	2,061	–	–	–	Dictionary	Lab	–	RGB	Introducing the DW-DGS – The Digital Dictionary of DGS	✓	SLR	–
LSFB-isol (Fink et al., 2021)	2021	French Belgian	395	–	47,551 videos	85	General	Lab	–	RGB	LSFB-CONT and LSFB-ISOL: Two New Datasets for Vision-Based Sign Language Recognition	✓	SLR	Top-1 51.5% (Fink et al., 2021)
GSL-isol (Adaloglou et al., 2021)	2019	Greek	310	6.44 hours	40,785 videos	7	General	Lab	840×840	RGB-D	A Comprehensive Study on Deep Learning-based Methods for Sign Language Recognition	✓	SLR	89.74% (Adaloglou et al., 2021)
IISL Nandy 2010 (Nandy et al., 2010)	2010	Indian	22	–	600 samples	–	General	Lab	–	RGB	Recognition of Isolated Indian Sign Language Gesture in Real Time	×	SLR	–

Table 16: Isolated Sign Language Dataset (Part III)

Dataset	Year	Language	Vocab. Size	Duration	#Samples	#Signers	Domain	Collection Source	Resolution	Modality	Publication	Available	Task	Baseline Model Accuracy
INSLR Dataset (Kishore and Kumar, 2012)	2012	Indian	80	–	1,600 videos	10	General	Lab	640×480	RGB	A Video Based Indian Sign Language Recognition System (INSLR) Using Wavelet Transform and Fuzzy Logic	×	SLR	96% (Kishore and Kumar, 2012)
INCLUDE (Sridhar et al., 2020)	2020	Indian	263	–	4,287 videos	7	General	Lab	1920×1080	RGB	INCLUDE: A Large Scale Dataset for Indian Sign Language Recognition	✓	SLR	–
CISLR (Joshi et al., 2022)	2022	Indian	4,765	–	7,050 videos	71	General	Lab	–	RGB	CISLR: Corpus for Indian Sign Language Recognition	Agreement Needed	SLR	–
IISL2020 (Kothadiya et al., 2022)	2022	Indian	11	–	∼12,100 videos	16	General	Lab	1920×1080	RGB	Deepsign: Sign Language Detection and Recognition Using Deep Learning	✓	SLR	F1-Score 97% (Kothadiya et al., 2022)
K-RSL (Mukushev et al., 2020)	2020	Kazakh-Russian	20	–	5,200 isolated sign samples	5	General	Lab	–	RGB, Skeleton-Keypoints	Evaluation of Manual and Non-manual Components for Sign Language Recognition	✓	SLR	78.20% (Mukushev et al., 2020)
KSL-Dataset (Yang et al., 2019)	2019	Korean	77	–	1,229 videos	22	General	Lab	255×255	RGB	The Korean Sign Language Dataset for Action Recognition	×	SLR	–
KSL Shin 2023 (Shin et al., 2023)	2023	Korean	20	∼1,600 seconds	400 videos	20	General	Lab	–	RGB	Korean Sign Language Recognition Using Transformer-Based Deep Neural Network	×	SLR	98.30% (Shin et al., 2023)
MSL (Mejía-Peréz et al., 2022)	2022	Mexican	30	–	3,000 samples	4	General	Lab	4056×3040, 1280×800	RGB-D	Automatic Recognition of Mexican Sign Language Using a Depth Camera and Recurrent Neural Networks	✓	SLR	96.44% (Mejía-Peréz et al., 2022)
WLPSL	–	Pakistani	31	–	248 videos	12	General	Lab	–	RGB	WLPSL: Word-Level Pakistani Sign Language Video Dataset	✓	SLR	–
PSL-30 (Oszust and Wysocki, 2013)	2013	Polish	30	–	300 videos	1	General	Lab	640×480	RGB-D, Skeleton	Polish Sign Language Words Recognition with Kinect	×	SLR	Top-1 98.33% (Oszust and Wysocki, 2013)
KSU-SSL (Al-Hammadi et al., 2020)	2020	Saudi	40	–	–	–	General	Lab	Varies	RGB, Kinect	Hand Gesture Recognition for Sign Language Using 3DCNN	×	SLR	–
LSE-Sign (Gutierrez-Sigut et al., 2016)	2015	Spanish	5,100	–	5,100 entries	2	Dictionary	Lab	–	RGB	LSE-Sign: A lexical database for Spanish Sign Language	Agreement Needed	SLR	–
SL-Animals-DVS (Vasudevan et al., 2020)	2020	Spanish	19	–	1,102 recordings	58	Animal	YouTube	128×128	RGB	Introduction and Analysis of an Event-Based Sign Language Dataset	✓	SLR	–
SSL Lexicon (Mesch and Wallin, 2012)	2012	Swedish	21,345	–	–	–	General	Lab	–	RGB	From meaning to signs and back: Lexicography and the Swedish Sign Language Corpus	✓	SLR	–
SMILE (Ebling et al., 2018)	2018	Swiss-German	100	–	–	30	General	Lab	Varies	RGB-D	SMILE Swiss German Sign Language Dataset	✓	SLR	–
BosphorusSign (Camgöz et al., 2016)	2016	Turkish	855	–	–	10	Health, Finance, General	Lab	1920×1080	RGB-D	BosphorusSign: A Turkish Sign Language Recognition Corpus in Health and Finance Domains	×	SLR	–
BosphorusSign22k (Özdemir et al., 2020)	2020	Turkish	744	∼19 hours	22,542 videos	6	Health, Finance, General	Lab	1920×1080	RGB-D	BosphorusSign22k Sign Language Recognition Dataset	Contact Author	SLR	Top-5 94.76% (Özdemir et al., 2020)
AUTSL (Sincan and Keles, 2020)	2020	Turkish	226	21 hours	38,336 samples	43	General	Lab	512×512	RGB-D, Skeleton	AUTSL: A Large Scale Multi-Modal Turkish Sign Language Dataset and Baseline Methods	✓	SLR	Top-5 83.93% (Sincan and Keles, 2020)

Table 17: Continuous Sign Language Datasets (Part I)

Dataset	Year	Language	Vocab. Size	Duration	#Samples	#Signers	Domain	Collection Source	Resolution	Modality	Publication	Available	Task	Baseline Model Accuracy
RWTH-Boston-104 (Dreuw et al., 2007)	2007	American	104	8.7 min	201 sent.	3	General	Lab	–	RGB	Speech Recognition Techniques for a Sign Language Recognition System	✓	SLR	17% WER (Dreuw et al., 2007)
RWTH-Boston-400	2008	American	∼400	–	843 sent.	5	General	Lab	–	RGB	–	×	SLR	–
CopyCat (Zafrulla et al., 2010)	2010	American	22	–	420 phrases	5	General	Lab	–	RGB	A novel approach to ASL Phrase Verification using Reversed Signing	×	SLR	–
NCSLGR (Neidle and Vogler, 2012)	2012	American	1,920	–	1,887 utt.	4	General	Lab	–	RGB	A New Web Interface to Facilitate Access to Corpora	✓	SLR	–
ASLG-PC12 (Othman and Jemni, 2012)	2012	American	–	–	100 M sent.	–	General	Lab	–	RGB	English–ASL Gloss Parallel Corpus 2012: ASLG-PC12	✓	SLR	–
How2Sign (Duarte et al., 2021)	2020	American	16,000	79 hours	>35,000 sent.	11	General	Lab	1280×720	RGB, RGB-D, 3D Keypoints	How2Sign: A Large-scale Multimodal Dataset for Continuous American Sign Language	✓	SLR, SLT, SLP	–
ASLing (Ananthanarayana et al., 2021)	2021	American	–	–	1,284 samples	7	General	Crowd	450×600	RGB	Dynamic Cross-Feature Fusion for American Sign Language Translation	×	SLT	–
OpenASL (Shi et al., 2022)	2022	American	33,000	288 hours	–	220	General	Web	–	RGB	Open-Domain Sign Language Translation Learned from Online Video	✓	SLT	$BLEU_4$ 6.72 (Shi et al., 2022)
ASL-Homework-RGBD (Hassan et al., 2022)	2022	American	–	–	935 samples	45	General	Homework	–	RGB-D	ASL-Homework-RGBD Dataset: 45 signers' ASL homework videos	✓	SLT	–
YouTube-ASL (Uthus et al., 2024)	2023	American	60,000	∼1000 hours	–	>2,500	General	Web	–	RGB	YouTube-ASL: A Large-Scale, Open-Domain ASL–English Parallel Corpus	✓	SLT	$BLEU_4$ 3.95 (Uthus et al., 2024)
DailyMoth-70h (Rust et al., 2024)	2024	American	19,694	75.8 hours	48,386 clips	1	News	TV	–	RGB	Towards Privacy-Aware Sign Language Translation at Scale	✓	SLT	$BLEU_4$ 28.8 (Rust et al., 2024)
Auslan-Daily Comm. (Shen et al., 2024b)	2024	Australian	3,064	–	14,041 sent.	49	General	TV / Web	1920×1080	RGB	Auslan-Daily: Australian SLT for Daily Communication and News	✓	SLT	$BLEU_4$ 9.95 (Shen et al., 2024b)
Auslan-Daily News (Shen et al., 2024b)	2024	Australian	12,346	–	11,065 sent.	18	General	TV / Web	1280×720, 1920×1080	RGB	Auslan-Daily: Australian SLT for Daily Communication and News	✓	SLT	$BLEU_4$ 2.81 (Shen et al., 2024b)

Table 18: Continuous Sign Language Datasets (Part II)

Dataset	Year	Language	Vocab. Size	Duration	#Samples	#Signers	Domain	Collection Source	Resolution	Modality	Publication	Available	Task	Baseline Model Accuracy
BTVSL (Zeeon et al., 2024)	2024	Bangla	48,623	60 hours	24,085 sent.	22	News	Web	–	RGB	BTVSL: A Novel Sentence-Level Annotated Dataset for Bangla SLT	×	SLT	$BLEU_4$ 25.16 (Zhou et al., 2023; Zeeon et al., 2024)
LIBRAS-UFOP	2021	Brazilian	56	–	3,040 seq.	5	General	Lab	–	RGB, RGB-D, 3D Keypoints	A multimodal LIBRAS-UFOP dataset of minimal pairs	×	SLR	–
BSL-1K (Albanie et al., 2020)	2020	British	1,064	∼1000 hours	273,000 sam.	40	General	TV	–	RGB	BSL-1K: Scaling up co-articulated SLR using mouthing cues	✓	SLR	Top-5 88.83% (Albanie et al., 2020)
BOBSL (Albanie et al., 2021)	2021	British	2,281/78,000	1,467 hours	1.2 M seq.	39	General	TV	–	RGB	BBC-Oxford British Sign Language Dataset	✓	SLR, SLT	–
Video-based CSL (Huang et al., 2018b)	2018	Chinese	178	100+ hours	25,000 inst.	50	General	Lab	1920×1080	RGB-D	Video-based Sign Language Recognition without Temporal Segmentation	×	SLR	–
CSLD (Yuan et al., 2019)	2019	Chinese	10,000	–	49,708 vid.	50	General	Lab	1920×1080, 512×424	RGB-D	Large Scale Sign Language Interpretation	Contact Author	SLR	$BLEU_1$ 14.28 (Yuan et al., 2019)
CSL-Daily (Zhou et al., 2021b)	2021	Chinese	2,000	–	20,645 vid.	10	General	Lab	1920×1080	RGB	Improving SLT with Monolingual Data by Sign Back-Translation	Agreement Needed	SLR, SLT	$BLEU_4$ 21.34 (Zhou et al., 2021b)
CSL-News (Li et al., 2025)	2025	Chinese	4,875	1,985 hours	751,320 pairs	–	News	TV	Vary	RGB	Uni-Sign: Toward Unified Sign Language Understanding at Scale	×	SLT	–
CoL-SLTD (Rodríguez et al., 2020)	2020	Colombian	–	–	1,020 vid.	13	General	Lab	448×448	RGB	Understanding Motion in Sign Language: A New Structured Translation Dataset	–	SLT	–
S-pot (Viitaniemi et al., 2014)	2014	Finnish	1,211	–	5,539 vid.	5	General	Lab	720×576	RGB	S-pot: A benchmark in spotting signs within continuous signing	Contact Author	SLR	47.70% (Viitaniemi et al., 2014)
VRT-NEWS (Camgöz et al., 2021)	2021	Flemish	6,875	∼9 hours	7,174 seq.	9	News	TV	1280×720	RGB	Content4All Open Research SLT Datasets	✓	SLT	$BLEU_4$ 0.36 (Camgöz et al., 2021)
Corpus VGT	–	Flemish	–	140 hours	–	120	General	Lab	–	RGB	–	✓	–	–
Mediapi-RGB (Ouakrim et al., 2024)	2024	French	27,343	86 hours	1,230 vid.	>10	General	Online Media	Vary	RGB	Mediapi-RGB: An extensive LSF video–text corpus	✓	SLT	$BLEU_4$ 4.14 (Ouakrim et al., 2024)

Table 19: Continuous Sign Language Datasets (Part III)

Dataset	Year	Language	Vocab. Size	Duration	#Samples	#Signers	Domain	Source	Publication	Available	Task	Baseline Acc.
LSFB-CONT (Fink et al., 2021)	2021	French Belgian	6,883	–	85,132 videos	100	General	Lab	LSFB-CONT and LSFB-ISOL: Two New Datasets for Vision-Based Sign Language Recognition	✓	–	–
SIGNUM (von Agris and Kraiss, 2010)	2008	Germany	450	55.3 hours	33,210 seq.	25	General	Lab	SIGNUM Database: Video Corpus for Signer-Independent Continuous SL Recognition	✓	SLR	–
RWTH-PHOENIX 2012 (Forster et al., 2012)	2012	Germany	911	3.25 hours	1,980 sent.	7	Weather	TV	RWTH-PHOENIX-Weather: A large-vocabulary SL recognition & translation corpus	✓	SLR/SLT	–
RWTH-PHOENIX 2014 (Forster et al., 2014)	2014	Germany	1,558	10.73 hours	6,861 sent.	9	Weather	TV	Extensions of the Sign Language Recognition & Translation Corpus RWTH-PHOENIX-Weather	✓	SLR/SLT	–
Public DGS Corpus (Jahn et al., 2018)	2018	Germany	–	>50 hours	–	327	General	Lab	Publishing DGS corpus data: Different Formats for Different Needs	✓	–	–
RWTH-PHOENIX14T (Camgoz et al., 2020)	2020	Germany	2,887	$\sim$10.5 hours	8,257 sent.	9	Weather	TV	Sign Language Transformers: Joint End-to-end SL Recognition & Translation	✓	SLR/SLT	WER 26.5 (Koller et al., 2019), $BLEU_4$ 9.58 (Camgoz et al., 2018)
SWISSTXT-WEATHER (Camgöz et al., 2021)	2021	Germany	1,248	$\sim$1 hours	811 seq.	1	Weather	TV	Content4All Open Research SLT Datasets	✓	–	–
SWISSTXT-NEWS (Camgöz et al., 2021)	2021	Germany	10,561	$\sim$9.5 hours	6,031 seq.	9	News	TV	Content4All Open Research SLT Datasets	✓	SLT	$BLEU_4$ 0.41 (Camgöz et al., 2021)
PHOENIX-News (Yin et al., 2024)	2024	Germany	190,000	486 hours	–	11	News	TV	T2S-GPT: Dynamic Vector Quantization for Autoregressive SL Production from Text	Contact Author	SLP	–